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A novel decomposition ensemble model with extended extreme learning machine for crude oil price forecasting

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ABSTRACT

As one of the most important energy resources, an accurate prediction for crude oil price can effectively guarantee a rapid new production development with higher production quality and less production cost. Accordingly, a novel decomposition-and-ensemble learning paradigm integrating ensemble empirical mode decomposition (EEMD) and extended extreme learning machine (EELM) is proposed for crude oil price forecasting, based on the principle of "decomposition and ensemble". This novel learning model makes contribution to literature by introducing the current powerful artificial intelligent (AI) technique of EELM in the ensemble model formulation. In the proposed method, EEMD, a competitive decomposition method, is first applied to divide the original data of crude oil price time series into a number of relatively regular components, for simplicity. Second, EELM, a currently proposed, powerful, effective and stable forecasting tool, is implemented to predict all components independently. Finally, these predicted results are aggregated into an ensemble result as final prediction, using simple addition ensemble method. For illustration and verification purposes, the proposed learning paradigm is used to predict the crude oil spot price of WTI. Empirical results demonstrate that the proposed novel ensemble learning paradigm statistically outperforms all considered benchmark models (including popular single models and similar ensemble models) in both prediction accuracy (in terms of level and directional measurement) and effectiveness (in terms of time saving and robustness), indicating that it is a promising tool to predict complicated time series with high volatility and irregularity.

1. Introduction

International crude oil prediction has become an increasingly hot issue within the research fields of energy analysis and economic management, which can effectively guarantee a rapid new production development with higher production quality and less production cost. First, due to its significant role in the global economy and society (Oman, 2003), an accurate prediction for crude oil market is extremely indispensable for stable and rapid economic development and thence new production development. In particular, a leap in crude oil price would result in an inflation and economy recession in oil-consuming nations, and further negatively impact global economy. In contrast, a fast falling of crude oil price would otherwise prohibit the economic development of oil-producing countries, and further generate political instability and social unrest (Gholamian et al., 2005; Chen and Hsu, 2012). Therefore, an accurate prediction for crude oil price can effectively help capture the market dynamics and make the corresponding policies for avoiding high volatility of crude oil price and thus reducing the market risk, which can further enable a stable macroeconomic environment for a rapid new production development. Second, as one of the most important energy inputs, an accurate prediction for crude oil price can effectively help make appropriate production plans for new products in terms of higher quality and less cost. In particular, a higher crude oil price may enhance the production cost with the same use of crude oil, and vice versa. Therefore, an accurate prediction for crude oil price can effectively help make and revise production plans of new products and techniques for determining various inputs, which can significantly enhance the quality and reduce the cost of new production development. However, it has been proved to be an extremely tough task of forecasting crude oil price, due to the interactive inner factors, such as supply and demand, competition across providers, substitution with other energy forms, technique development, domestic economy, deregulation activities, globalization and even uncertainties caused by political instabilities, wars and conflicts (Chen, 2009; He et al., 2012; Zhang et al., 2009). To address such tough task, this paper concentrates on crude oil price forecasting, in order to improve the prediction performance from both prediction accuracy and time saving perspectives.

According to existing literature, a variety of forecasting models have been formulated for international crude oil price prediction.

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Generally, there are two main categories for the crude oil price forecasting. The first category can be referred to traditional statistical and econometric techniques, such as linear regression (LinR), generalized auto regressive conditional heteroskedasticity (GARCH) family models, random walk (RW), grey model (GM) and error correction models (ECM). For example, a sophisticated econometric model was applied to predict crude oil price (Huntington, 1994). Lin (2009) predicted the international crude oil futures price via GM(1,1). Hou and Suardi (2012) implemented a nonparametric GARCH model to predict the return volatility in oil price. Mohammadi and Su (2010) proposed a novel hybrid model, coupling ARIMA and GARCH models, to estimate the conditional mean and volatility of weekly crude oil spot prices in eleven international markets. Similarly, Murat and Tokat (2009) employed RW to forecast oil price movements. Lanza et al. (2005) investigated the prices of crude oil and oil products by using ECM model. Besides, autoregressive integrated moving average (ARIMA) model, the most typical traditional time series model, has also frequently been applied as benchmark in crude oil price forecasting (e.g., He et al., 2012; Yu et al., 2008; Li et al., 2013).

However, these above traditional econometric techniques may be insufficient to capture the hidden nonlinear features in crude oil price (Bao et al., 2007; Yu et al., 2007), and there is a need to find a new approach to remedy the shortcomings of the traditional methods. In the previous studies, artificial intelligence (AI) models with powerful self-learning capacities, such as artificial neural networks (ANNs), support vector machine (SVM) and other intelligent optimization algorithms, have become increasingly popular for crude oil price forecasting recently, and the empirical results demonstrated their superiority to traditional methods. For ANN, Abdullah and Zeng (2010) introduced ANN to analyze the quantitative data of crude oil price. Kulkarni and Haidar (2009) presented a multilayer feed-forward neural network (FNN) to predict crude oil spot price. Kaboudan (2001) employed genetic programming (GP) and ANN to forecast crude oil price. As far as SVM, Xie et al. (2006) implemented SVM model for crude oil price forecasting and compared its prediction performance with ARIMA and back-propagation neural network (BPNN). Khashman and Nwulu (2011) employed SVM to predict crude oil price. Li and Ge (2013) improved ε-support vector regression (ε-SVR) machine with dynamic errors correction for crude oil price forecasting. All these studies demonstrated that the AI models are quite superior to the statistical-based models in modeling the nonlinear and complicated data of crude oil price.

Though the AI models (e.g., ANN and SVM) are very effective relative to traditional models, AI models also have their own shortcomings. For example, the time wasting, slow convergence and local minima may be the most important disadvantages, especially in ANN. In order to overcome these drawbacks, a novel learning algorithm called extreme learning machine (ELM), a special case of single hidden layer feedforward networks (SLFNs) proposed by Huang et al. (2004), tends to provide a better generalization performance and much faster learning speed than the above gradient learning algorithms, without setting stopping criteria, learning rate and learning epochs.

According to existing literature, there was few research about crude oil price forecasting by using ELM, although ELM has wildly been implemented in other forecasting cases, such as medium-term sales in fashion retail supply chains (Wong and Guo, 2010; Sun et al., 2008), electricity prices (Shrivastava and Panigrahi, 2014; Tian and Meng, 2010) and other applications (Wang and Han, 2015), and the empirical results all witnessed that ELM significantly outperformed its counterparts (e.g., ARIMA, SVR and ANN models) in both level and directional forecasting (Liu et al., 2012; Pati et al., 2013). Since ELM might be somewhat unstable with randomicity (Sun et al., 2008; Rong et al., 2008; Singh and Balasundaram, 2007; Miche et al., 2010), an extended ELM (EELM) method was accordingly proposed (Sun et al., 2007), where a given number of ELM models are run and the average value of the prediction results is calculated as the final result. Since EELM might be more stable and accurate than its original form, EELM model is especially introduced here as a very promising approach for forecasting international crude oil price.

Besides, a “decomposition and ensemble” principle can be also considered as a helpful tool for analyzing the data with high complexity and irregularity (Yu et al., 2008; Wang et al., 2005). Actually, the effectiveness of “decomposition and ensemble” has been already confirmed, and a series of decomposition-and-ensemble learning paradigms have been accordingly proposed. For instance, Yu et al. (2008) proposed a novel empirical mode decomposition (EMD) based neural network ensemble learning paradigm to predict the crude oil price. Tang et al. (2011) selected ensemble EMD (EEMD) and least squares support vector regression (LSSVR) respectively as decomposition and forecasting tools, to formulate a EEMD-based LSSVR learning paradigm for forecasting nuclear power consumption. Wang et al. (2014) integrated the EMD and Elman neural network to predict the wind speed. Lu and Shao (2012) put forward an ensemble approach integrating EEMD and ELM for forecasting computer products sales. Wang et al. (2011) proposed a seasonal decomposition (SD) based LSSVR learning approach for hydropower consumption forecasting. Tang et al. (2015) built a novel decomposition ensemble model by coupling the complementary EEMD and EELM, for crude oil price forecasting. Yu et al. (2014) constructed a similar methodology based on compressed sensing (CS) as data decomposition technique and some powerful AI forecasting tools, for crude oil price forecasting. All empirical results statistically verified that the methodology framework of “decomposition and ensemble” can significantly improve prediction performance. Therefore, this study tends to conduct the prediction research for international crude oil price under such effective “decomposition-and-ensemble” model framework.

Generally speaking, based on the “decomposition and ensemble” principle, this study tries to propose a novel “decomposition-and-ensemble” learning paradigm integrating EEMD and EELM, i.e., EEMD-based EELM ensemble learning paradigm, to forecast the international crude oil price. In this proposed methodology, the original data of crude oil price time series are first divided into several relatively independent intrinsic mode functions (IMFs) and one residue by EEMD, an efficient decomposition method relative to other decomposition methods (e.g., EMD and wavelet decomposition). Second, EELM, a fast and powerful forecasting tool relative to traditional statistical techniques and other AI models (e.g., ANN and SVM techniques), is applied to predict the different IMFs and residue independently. Finally, these predicted values are fused into an ensemble result as the final prediction by simple addition (ADD) ensemble method, since the sum of real values of the decomposed components is actually equal to the original data. The main contribution of the paper is to introduce the current powerful AI technique of EELM in the decomposition-and-ensemble method formulation. Different from other existing decomposition-and-ensemble models, this novel method especially utilizes the currently proposed EELM technique as the individual forecasting tool, with its unique merits of powerful prediction capability, time-saving training process and model robustness.

The main motivation of this study is to formulate a novel EEMD-based EELM ensemble learning paradigm to improve the performance of international crude oil price prediction, in terms of prediction accuracy, time saving, and robustness, and to compare its prediction performance with other popularly used forecasting techniques (including typical single models and similar ensemble models). The rest of this study is organized as follows. Section 2